

CONTROL CHART PATTERNS RECOGNITION WITH CONSTRAINED DATA

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DEDICATION

Dedicated to

To my beloved family

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ABSTRACT

Recognition and classification of non-random patterns of manufacturing process data can provide clues to the possible causes that contributed to the product defects. Early detection of abnormal process patterns, particularly in highly precise and rapid automated manufacturing is necessary to avoid wastage and catastrophic failures. Towards this end, various control chart patterns recognition (CCPR) methods have been proposed by researchers. Most of the existing control chart patterns recognizers assumed that data is fully available and complete. However, in reality, process data streams may be constrained due to missing, imbalanced or inadequate data acquisition and measurement problems, erroneous entries and technical failure during data acquisition process. The aim of this study is to investigate and develop an effective recognition scheme capable of handling constrained control chart patterns. Various scenarios of data constraints involving missing rates, missing mechanisms, dataset size and imbalance rate were investigated. The proposed scheme comprises the following key components: (i) characterization of input data stream, (ii) imputation and feature extraction, and (iii) alternative recognition schemes. The proposed scheme was developed and tested to recognize the constrained patterns, namely, random, increasing/decreasing trend, upward/downward shift and cyclic patterns. The effect of design parameters on the recognition performance was examined. The Exponentially-Weighted Moving Average (EWMA) imputation, oversampling and Fuzzy Information Decomposition (FID) were investigated. This research revealed that some constraints in the dataset can eventually change the distribution and violate the normality assumption. The performance of alternative designs was compared by mean square error, percentage of correct recognition, confusion matrix, average run length (ARL), t-test, sensitivity, specificity and G-mean. The results demonstrated that the scheme with an ANN-fuzzy recognizer trained using FID-treated constrained patterns significantly reduce false alarms and has better discriminative ability. The proposed scheme was verified and validated through comparative studies with published works. This research can be further extended by investigating an adaptive fuzzy router to assign incoming input data stream to an appropriate scheme that matches complexity in the constrained data streams, amongst others.

ABSTRAK

Pengecaman dan klasifikasi terhadap corak data proses pembuatan yang tidak rawak boleh memberi petunjuk terhadap faktor yang mungkin mengakibatkan kecacatan pada produk. Pengesanan awal terhadap corak proses tidak normal terutamanya bagi pembuatan berautomatik cepat dan persis tinggi adalah perlu bagi mengelakkan pembaziran dan kegagalan bencana. Oleh itu, pelbagai kaedah pengecaman corak carta kawalan (CCPR) telah dicadangkan oleh penyelidik. Kebanyakan pengecam corak carta kawalan sedia ada mengandaikan bahawa data adalah tersedia dan lengkap sepenuhnya. Walau bagaimanapun realitinya, aliran data proses mungkin terhalang disebabkan oleh kehilangan, tidak seimbang atau tidak mencukupi disebabkan masalah perolehan dan pengukuran data, kesilapan memasukkan data dan kegagalan teknikal semasa proses perolehan data. Tujuan kajian ini adalah untuk menyiasat lanjut dan membangunkan satu skema pengecaman corak carta kawalan terkekang yang efektif. Pelbagai senario kekangan data yang melibatkan kadar kehilangan, mekanisme kehilangan, saiz set data dan kadar ketidakseimbangan telah dikaji. Skema yang dicadangkan terdiri daripada komponen-komponen utama yang berikut: (i) pencirian aliran data masukan, (ii) imputasi dan pengestrakan ciri, dan (iii) skema pengecaman alternatif. Skema yang dicadangkan telah dibangunkan dan diuji untuk mengenal corak yang terkekang, iaitu rawak, kecenderongan meningkat/menurun, peralihan ke atas/bawah dan corak kitaran. Kesan rekabentuk terhadap prestasi pengecaman telah diperiksa. Kaedah imputasi purata pergerakan berfungsi berpotensi (EWMA), persampelan lebih dan Penguraian Maklumat Kabur (FID) disiasat. Kajian ini mendedahkan bahawa beberapa kekangan dalam dataset boleh akhirnya telah mengubah taburan dan menyalahi andaian normal. Prestasi rekabentuk alternatif dibandingkan dengan mean square error, peratusan pengecaman tepat, matriks kekeliruan, purata panjang larian (ARL), ujian-t, kepekaan, kekhususan dan min-G. Keputusan menunjukkan bahawa skema dengan pengecam ANN-kabur yang dilatih dengan corak terkekang yang dipulihkan oleh FID berjaya mengurangkan penggera palsu dan mempunyai keupayaan diskriminatif yang lebih baik. Skema yang dicadangkan telah disahkan melalui kajian perbandingan dengan kajian-kajian yang telah diterbitkan. Penyelidikan ini boleh diperluaskan lagi antaranya ialah dengan menyiasat penghalang kabur adaptif untuk menetapkan laluan aliran data masukan yang sepadan dengan kerumitan data terkekang.

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LIST OF ABBREVIATIONS

ANOVA	-	Analysis of Variance
ANN	-	Artificial Neural Network
ARL	-	Average Run Length
CCP	-	Control Chart Pattern
CCPR	-	Control Chart Pattern Recognition
CYC	-	Cyclic Pattern
DS	-	Dataset Size
DT	-	Decreasing Trend Pattern
EWMA	-	Exponentially Weighted Moving Average
FID	-	Fuzzy Information Decomposition
G-MEAN	-	Geometric Mean
IID	-	Independent and Identically Distributed
IR	-	Imbalance Rate
IT	-	Increasing Trend Pattern
MAR	-	Missing at Random
MCAR	-	Missing Completely at Random
MF	-	Membership Function
ML	-	Machine Learning
MLP	-	Multilayer Perceptron
MM	-	Missing Mechanism
MR	-	Missing Rate
MSV	-	Mean Square Error
NOR	-	Normal Pattern
NMAR	-	Not Missing at Random
SPC	-	Statistical Process Monitoring
SVM	-	Support Vector Machine
US	-	Upward Shift Pattern

LIST OF SYMBOLS

b	-	Baseline noise level
c	-	Amplitude of cyclic pattern
C	-	Size of observation window
h	-	Magnitude of shift pattern
H	-	Production horizon finite length
s	-	Gradient of trend pattern
t	-	Time of sampling
T	-	Period of cyclic pattern
Y	-	Pattern variable
α	-	Smoothing factor
μ	-	Mean
σ	-	Standard Deviation
P_0	-	A series of subgroup averages sampled
P_t	-	Unstable pattern
X_k	-	Sample of n observations
\bar{x}_i	-	Subgroup average
\underline{x}_i	-	Missing at least one observation

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CHAPTER 1

INTRODUCTION

1.1 Background of the Problem

In today's global competitive marketplace, manufacturers strive to deliver the highest quality products at the lower production cost to gain an edge in the competition. With an appropriate quality control system, companies can maintain and continually improve the quality of products and processes and reduce the production cost. For the reason, manufacturing processes should be monitored effectively to avoid deviations in the production process and benefit from consistent quality.

Statistical process control (SPC) techniques are widely used in production industries to monitor processes and improve quality. One of the most important SPC tools is control chart which is used to differentiate between common cause and special cause of process variation. Measured quality characteristics are plotted in the control charts. A control charting procedure consists of getting a sample of n measures of a quality characteristic of a product at fixed time intervals and plotting on a graph a statistic computed through the n measures vs. a control interval delimited by two control limits. Control charts for long run processes were originally proposed by Shewhart while working for Bell Laboratories in 1920s. Later, exponentially-weighted moving average (EWMA) control charts were respectively proposed to improve the detection capabilities with respect to small to moderate process shifts to the out-of-control condition. While other control charts treat rational subgroups of samples individually, the EWMA chart tracks the exponentially-weighted moving average of all prior sample means. EWMA weights samples in geometrically decreasing order so that the most recent samples are weighted most highly while the most distant samples contribute very little. If any point falls outside the control limits or a non-random pattern is seen in the data located within the control limits, the chart display an unstable

process (Montgomery, 2007). Identifying the points which are located beyond control limits are not as challenging as recognition of control chart patterns (CCPs). Because CCPs are distorted by random noise in the process which is due to common cause of variation in manufacturing (Gauri & Chakraborty, 2008). Recognition of non-random patterns of process data can provide clues to the possible causes that contributed to the process instability. Early detection of process variation and assignable cause leads to improvement in the process yield and associated time and cost. The challenge is that in the ever-increasing rapid manufacturing, production time is too short to collect sufficient and balanced data. Figure 1.1 shows the trends leading to the problem.

Moreover, data acquisition problems, erroneous entries, inapplicable measurement, disclosure restrictions and deliberate withholding of some information makes the situation more complex when a proportion of the limited available data also might be partially lost, and all together lead to severe constrained data (Abdelrahman Senoussi *et al.*, 2017). Recognition of control chart patterns with missing, inadequate and imbalanced data is a challenging task.

The area of pattern recognition with constrained data is recognized as one of the 100 key scientific research fronts and the first one in terms of citations in mathematics, computer science and engineering in 2013 (King & Pendlebury, 2013). The core researches in this area consisted of methods and algorithms designed for the recovery or restoration of signals, images, and videos with sparse data source or where noise or blur must be corrected, or missing data filled in.

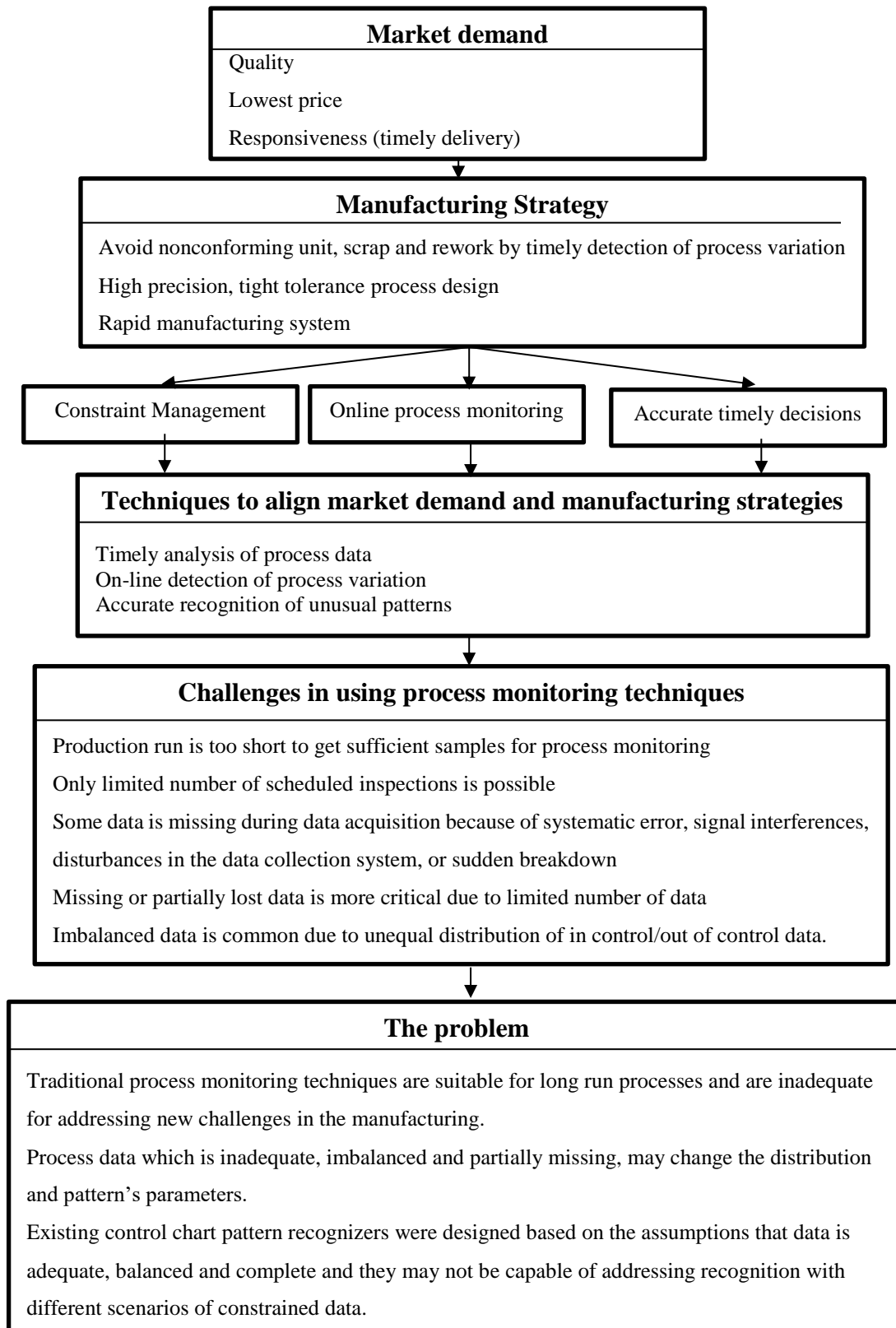


Figure 1.1 Trends leading to problem

In recent years, constrained data has received a growing attention in SPC where researchers studied construction of control charts with missing data (Madbuly *et al.*, 2013; Mahmoud *et al.*, 2014; Wilson, 2009), recognition of CCPs with imbalanced data (Xanthopoulos & Razzaghi, 2014), recognition of bivariate CCPs with missing data (Abdelrahman Senoussi *et al.*, 2017) and a conceptual study on recognition of CCPs with constrained data (Haghighati & Hassan, 2014). Even though recognition of constrained data has been investigated in various fields of studies, our literature review was unable to find rigorous investigation on recognition of constrained control charts patterns.

1.2 Statement of the Problem

Most of the existing control chart pattern recognizers were designed based on the assumption that training data is sufficient, balanced and complete. However, in actual production processes, data may be inadequate, imbalanced and missing due to data acquisition problems, erroneous entries, inapplicable measurement, disclosure restrictions and deliberate withholding of some information. Even though constrained data issues have been investigated in various field of studies, but no rigorous study has been found on CCPR. Existing frameworks are unable to address the issues that arose with reduction of dataset size which diminishes the effectiveness of current input representation, training and recognition algorithms. To address this gap, improved recognition schemes are needed to improve recognition of constrained control chart patterns. So that, there is a need to provide improved procedures for input representation, data treatment and training of the recognizers, according to different scenarios of missing data. An effective solution should give fast and accurate recognition of process variability patterns with minimum false alarms, even when the available process data is constrained.

1.3 Purpose of the Research

This research aims to develop alternative recognition schemes for process data streams within several constrained data scenarios, namely missing, inadequate and imbalanced. In particular, improved procedures should be investigated with desirable performance of accurate prediction and recognition of constrained data streams within control limits of shewhart X-bar chart.

1.4 Objectives of the Study

The research objectives are listed as below:

1. To formulate an effective imputation algorithm that can address missing data in control chart patterns.
2. To develop recognition schemes to address recognizer training with inadequate, imbalanced and missing data.
3. To assess characteristics of constrained data scenarios in alternative recognition schemes.

1.5 Scope and Key Assumptions

The scope of study covers the followings:

1. Manufacturing process data were assumed to be univariate and X-bar Shewhart control chart was used to investigate process variation.
2. Standard synthesized and published reference manufacturing data was used for modelling and validation.
3. Constrained data is limited to three types of constraints, namely, missing data, inadequate data and imbalanced data.

4. Solution approach for pattern recognition is limited to soft computing techniques.

1.6 Significance of Research

This study is significant and important from theoretical and practical aspects. This research is rationalized and motivated from the following perspectives:

From theoretical perspective, developing improved recognition schemes for constrained data, can address shortcoming of existing frameworks. Existing recognition frameworks are lacking in addressing challenging issues in training and recognition of data streams that are missing, inadequate and imbalanced. Therefore, it is important to design and develop improved schemes with relevant input representation and training procedures for different scenarios of constrained data.

From practical perspective, in the era of rapid manufacturing where the production time is too short to collect sufficient data, effective techniques are required to facilitate accurate process monitoring and recognition, in early phases of process deviation and deterioration. Improved procedures and techniques should be able to recognize and predict process instability when sufficient representative process data is not available due to various reasons.

1.7 Operational Framework for Research Activities

The recognition schemes were developed and tested in four phases as it is shown in Figure 1.2. First, a method was designed for simulation and characterization of datasets with missing data. The missing data factors that can change the distribution and normality of data were identified in this step. In the second phase, various imputation techniques were applied to estimate the missing data. The performance of imputation techniques was measured by mean square error (MSE) in which estimation

error of selected statistical properties from the actual complete dataset was compared in various techniques. An imputation technique with the least estimation error was selected and further investigated with various missing data properties. In addition, a minimal feature set was selected to represent the imputed dataset with the lowest deviation of feature values from complete dataset features. Then the minimal feature set was used to train the MLP-based network to recognize six possible patterns, namely, random, increasing/decreasing trend, shift up/down and cyclic patterns from the process data streams with missing data. The MLP network performance was measured in several missing data scenarios with/without imputation and features.

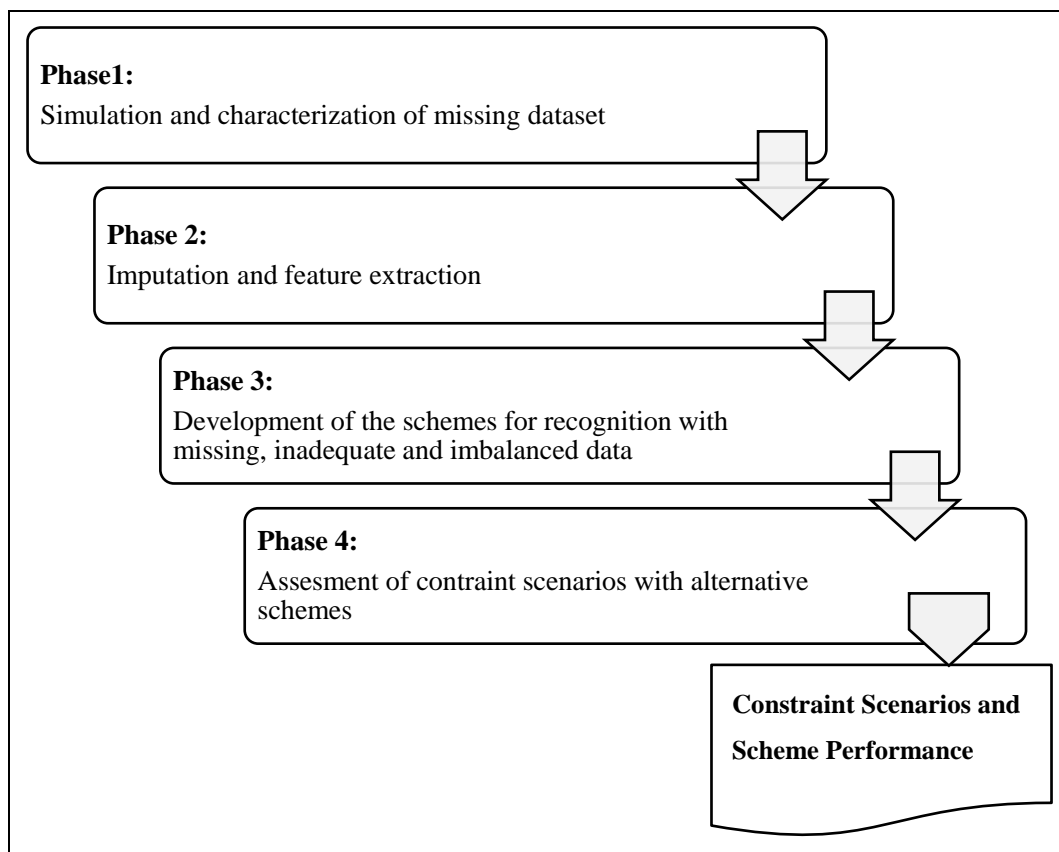


Figure 1.2 Operational framework for research activities

In the third phase, the feature set was updated to suit the recognition of streaming data. The performance of the recognizer trained with features extracted from partially developed CCPs was measured with or without missing data. Then the effect of training the MLP recognizer with balanced and imbalanced dataset was examined. Also, size of training dataset was varied and the simultaneous effect of imbalanced and inadequate dataset in training and recognition performance was studied. To improve

recognition performance, an oversampling technique and use of a hybrid ANN-fuzzy recognizer was proposed to address training with missing, inadequate and imbalanced data. Three schemes from the solution approaches were developed and their performance were compared after training with various dataset size and imbalance rates. Finally, in the fourth phase, assessment of constraint scenarios with alternative schemes was studied and the performance in the recommended scheme was compared with alternative schemes in the literature. Each phase serves a building block towards achieving the research objectives.

1.8 Definition of Terms

1. Constrained data

Constrained data in this research refers to process data streams which are missing, inadequate or imbalanced.

2. Constraint Control chart patterns (CCPs)

Control chart patterns were introduced in Western Electric Company (1958). Six basic CCPs are (a) normal, (b) cyclic, (c) increasing trend, (d) decreasing trend, (e) upward shift, and (f) downward shift patterns.

3. Imputation

In statistics, imputation is the process of replacing missing data with plausible substituted values.

4. Input representation

It is a process of transforming raw input data into a new format for representation of input into the recognizers. It involves pre-processing activities such as normalisation, standardization, feature extraction and feature selection.

5. Missing Mechanism

Missing mechanism group data by investigating whether the data is missing at random or not.

6. Missing at random

When the missingness is independent of the missing variable but it can be traced or predicted by other variables in the process, the missing mechanism is called missing at random (MAR).

7. Missing completely at random

When the probability that a value is missing is independent from the variable itself and any other variable in the process or external influence, the missing mechanism is called missing completely at random (MCAR).

8. Not missing at random

When there is a relationship between the value in the variable which is missing with the other observed values in the same variable, the missing mechanism is called not missing at random (NMAR).

9. Online monitoring

Online monitoring refers to a continuous tracking of process data streams to identify whether a process has deviated from a normal operating condition.

10. Online recognition

Online recognition is a process of recognising an unknown CCP and to assign it to one of the prescribed classes.

11. Inadequate data

Majority of supervised recognizers rely on a vast volume of data in order to learn all the possible stable and unstable process patterns. However, in short-run production and start-up processes, the historical dataset size is too small to train the recognizer. This issue is called inadequate data problem in this research and it is one of the data constraints.

12. Imbalanced data

One of the most common problems faced in real world databases is imbalanced data. The reason is that often one pattern particularly the one which represent the process in its stable state has more historical sample in comparison to the other patterns which represent the process in its unstable status. Performance of the recognizer which is trained with such dataset, is usually biased towards the majority class.

13. Scheme

Scheme is a recognition and constrained data treatment strategy which is formulated to address recognition of CCPs.

14. Baseline Scheme

Baseline scheme refers to CCPR scheme that is developed based on a ANN pattern recognizer and EWMA imputation which is capable of treatment of missing data.

15. Enhanced Schemes

Enhanced Schemes refer to recognition with hybrid ANN and fuzzy either with/without constrained data treatment using fuzzy information decomposition.

1.9 Structure of the Thesis

This thesis is organized into seven chapters. Chapter 1 provides an introduction to the research. Chapter 2 discusses background and review of relevant literature that is used to formulate research problem. Chapter 3 serves as the research methodology. Chapter 4 presents an investigation toward developing a baseline scheme for recognition of CCPs with missing data. Chapter 5 is an enhancement of the proposed baseline scheme for recognition of CCPs which can address inadequate and imbalanced data. Research findings are discussed in the Chapter 6 and the final chapter concludes this research. Figure 1.3 shows the structure of this thesis.

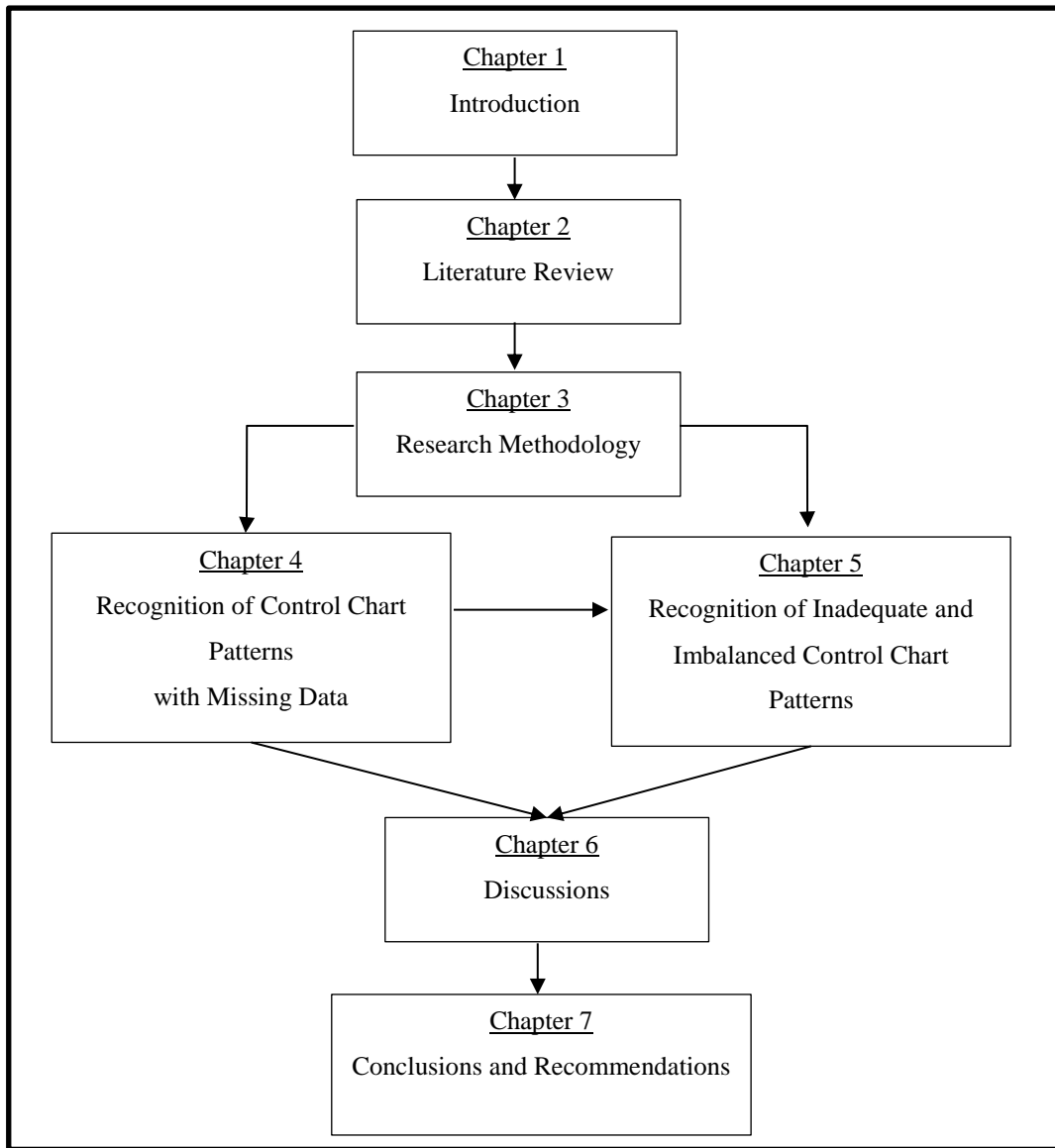


Figure 1.3 Structure of the thesis

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List of Publications and Papers Presented

To date, this research has contributed three publications as follows:

Journal with Impact Factor

1. Haghghiati, R., & Hassan, A. (2018). Recognition performance of imputed control chart patterns using exponential weighted moving average European Journal of Industrial Engineering, Vol. 12, No. 5, pp.637-660. (Q3, IF: 1.085)

Indexed Conference Proceedings

1. Haghghiati, R., & Hassan, A. (2014). A conceptual methodology for recognition of constrained control chart patterns *Advanced Materials Research* (Vol. 845, pp. 696-700).
2. Haghghiati, R., & Hassan, A. (2019). Feature extraction in control chart patterns with missing data *Journal of Physics. Ser. 1150*. 012013.